

**Prediction and Optimization of a Ceramic Casting Process**  
**Using A Hierarchical Hybrid System of Neural Networks and Fuzzy Logic**

Sarah S. Y. Lam, Kimberly L. Petri and Alice E. Smith (Senior Member IIE)<sup>1</sup>

Department of Industrial and Systems Engineering

Dunstan Hall

Auburn University

Auburn University, AL 36849-5346 USA

334-844-1400

334-844-1381 (fax)

Accepted to *IIE Transactions on Design and Manufacturing*

May 1999

---

<sup>1</sup> Corresponding author.

**Prediction and Optimization of a Ceramic Casting Process**  
**Using A Hierarchical Hybrid System of Neural Networks and Fuzzy Logic**

**ABSTRACT**

This paper is a case study that describes a hybrid system integrating fuzzy logic, neural networks and algorithmic optimization for use in the ceramics industry. A prediction module estimates two quality metrics of slip-cast pieces through the simultaneous execution of two neural networks. A process improvement algorithm optimizes controllable process settings using the neural network prediction module in the objective function. An expert system module contains a hierarchy of two fuzzy logic rule bases. The rule bases prescribe processing times customized to individual production lines given ambient conditions, mold characteristics and the neural network predictions. This paper demonstrates the applicability of newer computational techniques to a very traditional manufacturing process and the system has been implemented at a major U.S. plant.

Keywords: Ceramic Slip-casting, Neural Networks, Fuzzy Logic, Expert System, Optimization Algorithm, Hierarchical Model, Hybrid System, Cross Validation.

## **1. INTRODUCTION**

Slip-casting is used as the primary manufacturing process for many complex ceramic goods including sanitaryware, giftware, and tableware where ceramic pressing is not practical.

Slip-casting is a second choice after pressing because it is considerably more difficult to achieve good results in both product quality and in productivity. However, pressing can only manufacture simple shapes, such as plates, while slip-casting can manufacture items such as bowls, pitchers, statues, and sinks. The manufacture of slip-cast ceramicware consists of the following steps: (1) preparation of the slip (liquid clay), (2) casting the slip in a plaster mold for a specified duration, (3) removing the mold, (4) air drying the cast piece, (5) glazing the dried product, (6) firing the glazed product in a kiln, and (7) inspection of the finished product. Of particular interest is step 2 of the process (slip-casting), where liquid slip is poured into plaster molds and allowed to cast for a specified time period to form a solid product (Lambe, 1958). It is the slip-casting process that largely determines the quality of the final product, since cracks, slumps, and instabilities in the cast are manifest only subsequent to the casting process. Defects that are found before the ware is fired can often be repaired. For defects that cannot be repaired, the clay material can be recovered, but the considerable labor and overhead are still lost. Most defects that are found after firing result in a complete loss of the defective piece. The proportion of defective pieces due to casting imperfections can approach 30%, a significant problem affecting the efficiency and profitability of slip-casting manufacturing firms<sup>2</sup>. Additionally, the slip-casting step is the most time consuming and operator intensive aspect of the process.

This paper describes a modular system for the slip-casting process that integrates neural networks, a dual-objective optimization algorithm, and fuzzy logic techniques as shown in Figure 1 to improve both the quality and the efficiency of the slip-casting step. A hybrid approach was used because the modules can be used individually or collectively according to the decision to be made. The predictive module estimates *cast rate* and *moisture gradient* — the two primary

---

<sup>2</sup> The 30% figure comes from internal industry sources that cannot be cited.

determinants of cast quality and efficiency — given ambient conditions, process settings and slip characteristics. The process improvement module determines the best set of controllable settings for the given ambient conditions and slip characteristics. The fuzzy logic expert system recommends the processing time customized to a production line given the localized ambient state and the condition of the plaster molds. The system also includes a data repository to store and analyze daily process records, an automatic control charting feature, and a training module to expedite the learning curve of new workers.

---

Insert Figure 1

---

While these newer computational approaches have been proposed for industrial use in many papers, there are few examples of implemented systems in traditional manufacturing environments. The slip-casting industry has experienced little technological improvement and still depends on human expertise and judgement, and on trial-and-error casting tests. This hybrid system is the first known intelligent decision-support system for ceramic casting. It has been implemented at a major U.S. manufacturer of sanitaryware to enable superior product quality, reduced waste, and improved manufacturing efficiency. Section 2 describes the slip casting process and previous approaches to process improvement and control. Section 3 describes each module of the hybrid system, discussing the development effort and giving results. A summary of the general contributions of the research and the lessons learned from working on a complex traditional manufacturing process concludes the paper.

## **2. BACKGROUND**

### **2.1 The Slip-Casting Process**

The slip-casting process is used to produce ceramicware in intricate shapes that cannot be obtained through other methods, such as pressing. In the slip-casting process, a slurry, or slip, is prepared by mixing clay powder with a suspending liquid. Deflocculants are added to the slurry to provide stability and density, and binders are added to ensure that the resulting cast is strong enough to be handled. The slurry is then poured into a plaster mold. Most of the liquid in the slip is absorbed into the mold through capillary action, leaving a solid cast inside the mold. When it is estimated that the cast has reached the desired thickness and stability, the mold is removed and the piece is dried, glazed and fired (Adams, 1988).

The primary causal factor for cast fractures and/or deformities is the distribution of moisture content inside the cast prior to firing. When the moisture differential, or *moisture gradient*, through the cross-section of the cast is too steep, it results in stress differences that cause the piece to deform and to eventually fracture (often during firing). In order to have a good cast, the moisture content should be as uniform as possible through the cross-section, i.e., a moisture gradient near zero. Another important manufacturing measure is *cast rate*, which is actually the thickness of the cast achieved during a specified time in the mold. A larger cast rate results in quicker casts and more efficient production.

## **2.2 Statics and Dynamics of the Slip-Casting Process**

The quality of the cast and the cast rate depend on the slip conditions, the ambient conditions in the plant, and the plaster mold state prior to casting. To decide on the values of the process-controllable variables each day, ceramic engineers run a series of tests that emulate the behavior of the slip during casting. On the basis of these time consuming, human-dependent, and trial-and-error tests, the engineers can obtain a “test cast” of acceptable quality. Then, a production batch is started with the same properties as the acceptable test product. Two ambient

variables, ten slip property variables and casting time (Table 1) are the relevant process parameters.

---

Insert Table 1

---

There are individual factors, however, which make uniform production impossible. These factors, which change over time and among operators, are: localized ambient conditions of the production line and the state of the plaster molds. An overall decision on casting time is made by the ceramic engineers, and then customized to an individual production line (30 to 40 molds) using the ad hoc judgment of the foremen or operators. The primary determinants of mold state are the age of the mold and the localized ambient conditions. As the age of a mold increases, its capillary action degrades, which causes an increase in the required casting time. Molds that are cast under hot, dry ambient conditions (i.e., near a kiln) require less casting time than molds cast under cooler, wetter conditions (i.e., near the building exterior). The variance of ambient conditions across the plant can be a significant problem in ceramic casting facilities, which are large and not environmentally well controlled.

### **2.3 Previous Relevant Work**

Previous work in ceramic process optimization has been very limited due to the inability of theoretic and analytic models to adequately describe the complex dynamics of the casting process. Readey (1993) introduced a process optimization method using a graphic format to improve manufacturing yields for ceramics by considering a small subset of the process variables. He decided that the analysis would become too complex if more than a few process variables were considered. Knotts (1995) used statistical experimental design to select optimum ball clays (a raw

material) for increasing casting rates in a sanitaryware application. Dinger (1990) developed a rule-based expert system to examine the effects of particle size distribution on slip rheology. Stinson et al. (1994) applied neural networks to laser scatter patterns to characterize the microstructure of optical translucent ceramics. Martinez et al. (1994) used a neural network to predict cast quality using a categorical metric. Xia et al. (1995) constructed a materials design system, which includes a ceramics database, optimization modules, a knowledge base and an artificial neural network, to improve generic properties of ceramics.

Several studies on the application of hybrid systems using fuzzy logic and/or neural networks in manufacturing have been conducted. Lin et al. (1996) applied a backpropagation neural network to identify the system model for evaluating a fuzzy logic controller of a cement roller mill. Shin and Vishnupad (1996) presented a generic scheme for intelligent optimization and control of complex manufacturing processes. They proposed using neural networks to model the nonlinear process and then using fuzzy logic for process control. Chen et al. (1997) discussed the hierarchical use of two neural networks for copolymer composition distribution predictive control. A critical parameter is identified by the first neural network, which is then fed to the second network for control. Azouzi and Guillot (1996) presented an adaptive neurocontrol scheme for on-line optimization of machining. Their method uses a hybrid neural network that learns the relationships between process inputs and process states both off-line and on-line.

### **3. DEVELOPMENT OF THE HYBRID INTEGRATED SYSTEM**

This section starts with the data repository, then follows with a description of the modules for neural network prediction, process improvement, and cast time customized to each production line.

#### **3.1 Data Repository and Training Module**

The data repository is a large relational database that includes the daily parameters of Table 1 describing ambient conditions, process settings and slip characteristics. The outcome variables of moisture gradient and cast rate, as measured from the test cast, are also stored. The database consists primarily of production data supplemented with a few well chosen experiments to provide observations on the extremes of the production environment (e.g., very high or low temperature) (Coit et al., 1998). The user can visualize data (for each parameter) as Shewhart control charts (Montgomery and Runger, 1994) or as scatterplots over any specified time period. Both manners of presenting the data have been valuable to plant personnel because there is considerable short-term variability that masks long-term trends when examining only a few weeks of data (as was previously done). This daily data is also used as input to the remaining modules. While this might be relatively uninteresting from a research perspective, the compilation, purification and structuring of this database was a significant effort and one that affords the plant real benefits in the ability to analyze their casting process over both the long run and the short run. A training module has been included in the system and consists of ten archetype (good, average and poor) casting days from the data repository. This allows novice engineers, foremen, and operators to interact with typical casting days to try to improve results by virtually altering process variables interactively with the system. The plant was especially interested in this feature as the learning curve for slip-casting is long and casting results are strongly dependent on experiential knowledge.

### **3.2 Neural Network Prediction Module**

The following facts motivated the development of two separate but parallel neural networks — the cast rate neural network (CRNN) and the moisture gradient neural network (MGNN) (see Figure 2): many of the process variables are uncontrollable (for instance, ambient

conditions and particle distribution of the raw material), most slip properties cannot be changed on a day-to-day basis, and the interactive behavior of the process variables is mostly unquantified. The neural network is an empirical universal approximator, that is, a neural network theoretically can model any relationship through examination of the inputs and outputs only (Funahashi, 1989, Hornik et al., 1989). Neural networks have been used in many manufacturing applications (see Zhang and Huang (1995) for a good overview) and have been noted to be robust to imperfections in the data and accommodating of large dimensional data sets. These attributes were especially important to this application, where the form of the relationship between the many process variables and cast quality was undefined and where the data set available from production contained missing and corrupt observations. The neural network predictions can be used alone as surrogates for the daily physical test casts; the predictions are also used in conjunction with the process improvement algorithm and with the expert system for production line control.

---

Insert Figure 2

---

### **3.2.1 Neural network architecture and training**

The data sets available contained 952 observations (~3.5 years) for the CRNN and 367 observations (~1.5 years) for the MGNN. Moisture gradient is a difficult measure to make on a daily basis and so it had been enacted more recently in the plant than the easier daily cast rate measurement. The neural network architectures, training parameters, and stopping criteria were selected through experimentation and examination of preliminary networks. An ordinary backpropagation learning algorithm was used because of its documented ability as a continuous function approximator (Funahashi, 1989, Hornik et al., 1989).

The final network architecture used for the CRNN was a multi-layered fully-connected perceptron with 13 inputs, two hidden layers with 11 hidden neurons in each layer, and a single output (the cast rate in inches). The MGNN model was developed in a similar way using the same input variables, two hidden layers with 27 hidden neurons in each layer, and a single output (moisture gradient in percent change).

### **3.2.2 Neural network validation procedure**

The more traditional random separation (*data splitting*) of the data into a testing set and a training set (e.g., 20%, 80% respectively) was not used. This was because the system was built for industrial use and the plant engineers and supervisors **had to be assured** that the neural network predictions were accurate. Therefore, a five-fold group *cross validation* was used to validate the neural networks as this allows all data to be used for both validation and construction of the neural network prediction models. This cross-validation method, although intensive in computational effort, leverages the data by using all observations for both training and testing ((Wolpert, 1993), (Efron, 1982), (Geman et al., 1992), (Twomey et al., 1995)). The estimate of neural network prediction error is nearly unbiased and is more reliable than that obtained from the data splitting method (Twomey and Smith, 1998). Furthermore, the final neural networks used in the system are constructed using *all* the data rather than a training subset, ensuring the best possible prediction performance.

The available data for each neural network was divided into five mutually exclusive groups using systematic sampling after randomizing the entire data set. For both the CRNN and the MGNN, five validation networks with parameters identical to those of the final models described in section 3.2.1 were built, each using four groups of the data as a training set, and the remaining group as a test set. In other words, each cross-validated network was trained using 80% of the

available data and tested on the remaining 20%. Combining these five mutually-exclusive test sets would give the original available data set. The errors of the five testing sets provide the estimate of the generalization ability of the final network.

### 3.2.3 Results discussion

#### *CRNN*

Figure 3 shows a typical cross-validation network and its predictions on the 20% test set against the observed cast rate. In examining the results over the five cross-validated networks, it was verified that the CRNN performed well on all the available data (952 observations) and had unbiased generalization for all combinations and values of the independent variables used in this application. The summation of the test sets over the five validation networks showed a mean absolute error (MAE) of 0.017 (4.84%) and a root mean square error (RMSE) of 0.024 (6.83%). These values were precise enough for plant use.

---

Insert Figure 3

---

#### *MGNN*

Similar analysis of each 20% holdback test set showed that the MGNN performed fairly well across all the available data (367 facts). Figure 4 shows the predictions of the MGNN against the observed moisture gradient for one of the 20% holdback test sets. The summary of the five test sets were an MAE of 0.0036 (68.64%) and an RMSE of 0.0061 (116.30%). The reduced precision of the MGNN was due to several factors. A smaller sample of data was available than for the CRNN and there was considerable human error possible in the moisture gradient measurement. This imprecision, however, did not preclude MGNN use in the system.

To understand why, Table 2 shows the MAE, RMSE and percentage correct for five ranges of moisture gradient whereas Table 3 shows the distribution of incorrect predictions (for the test sets). The MGNN does a fairly good job of prediction for small moisture gradients, and can discriminate between a good moisture gradient and a bad moisture gradient since nearly all errors are only a category prediction away. Taking a categorical approach, the MGNN had prediction ability of adequate precision for use in the plant.

---

Insert Figure 4

---

---

Insert Tables 2-3

---

### **3.3 Process Improvement Module**

This feature recommends settings of controllable variables, given fixed settings of the other process variables, to maximize quality and productivity. The variables most commonly altered on a daily basis are *sulfate content* and *casting time*. An enumerative optimization algorithm sequentially generates all possible combinations of casting time and sulfate content on a discretized lattice of 26 by 26 bounded by the production extreme values. The combinations of sulfate content and casting time are sent to the neural network prediction module along with that day's values of the uncontrollable, or state, process variables. Enumeration is used because the search space is relatively small and the process cannot support settings finer than the lattice used (e.g., casting time is not specified in units smaller than a minute). If the search space were larger, a more efficient optimization routine could be used such as Newton's method (Chong and Zak,

1996) (handling the optimization problem as continuous) or simulated annealing (handling the optimization problem as combinatorial) (Reeves, 1993).

The neural network prediction module estimates the cast rate and the moisture gradient for each combination. The optimization algorithm selects the best three combinations that minimize the moisture gradient (primary objective) and maximize the cast rate (secondary objective). Providing the three best process settings allows the ceramic engineer to review the options prior to implementation, maintaining some human expertise in the decision. If the user wished to further study the three recommended settings by considering other factors, he or she could use a method such as the Analytic Hierarchy Process (Saaty, 1980).

### **3.4 Fuzzy Logic Expert System Module**

This module incorporated important factors affecting cast quality that are individual to a particular production line, as detailed in Petri and Smith (1996). These factors are the age of the plaster molds (which ranges from 0 to 6 weeks) and the ambient conditions of where the line is located in the plant. It was necessary to use a knowledge-based approach rather than a pure numeric model because there was no data that related mold age and local ambient environment to cast quality, and it was impractical to begin to record such data in the plant. Instead, these two important factors were included in two rule bases that work as a hierarchy as shown in Figure 5. The rule bases replicate the knowledge of the ceramic engineers, foremen and operators at the manufacturing facility, and provide cast time decisions customized for a specific operator's line of 30 to 40 molds<sup>3</sup>. The use of fuzzy logic was included to allow for more precise handling of the variables, reduce the number of rules required, and result in a smoother decision surface.

---

Insert Figure 5

---

Ambient temperature (°F), ambient relative humidity (%), and the age of the molds in weeks for that production line are presented as crisp, continuous inputs to the first fuzzy rule base that predicts mold condition. Mold condition is rated on an ordinal scale of zero to ten, with zero being the driest and ten being the wettest. This prediction of mold condition is then paired with a crisp, continuous prediction of the cast rate from the CRNN; together these are used in the second fuzzy rule base in order to generate a recommended cast time in minutes for that particular production line. Defuzzification to a crisp output is done using the centroid method (Ross, 1995) by computing the center of mass of the region of the output variable defined by the fuzzy output.

### **3.4.1 Development of the rule bases and the membership functions**

Three ceramic engineers were asked to develop rule bases for both mold condition and cast time independently of each other. A comparison of the three rule bases was then provided to each of the ceramic engineers, and they were given the opportunity to modify their responses, a simple Delphi technique. The three updated rule bases were consolidated into a single rule base. Tables 4 and 5 show the fuzzy associative memories (FAM's) for each rule base. For example, Table 4 shows that if the ambient *temperature* is *low*, the ambient *humidity* is *high*, and the *mold age* is *old*, then the *mold condition* is *very wet*.

---

Insert Tables 4-5

---

The membership functions for the ambient temperature, ambient humidity and cast rate

---

<sup>3</sup> All molds of a given production line are the same age and located in the same place in the plant, therefore, they

were developed through examining the frequency distributions of approximately two years of historical plant data. Each of these membership functions used three trapezoidal fuzzy sets (examples are shown in Figure 6). The membership functions for mold age, mold condition and cast time were developed in conjunction with the plant's ceramic engineers since data was not available. The number and shape of the trapezoidal fuzzy sets for mold condition and cast time were set by the ceramic engineers in order to incorporate the full range of process dynamics.

---

Insert Figure 6

---

Figure 7 shows a decision surface for the cast time rule base. Here the  $x$ -axis is the cast rate, the  $y$ -axis is the mold condition, and the  $z$ -axis is the recommendation for cast time for the production line. Note that the decision surface is clearly non-linear yet has smooth transitions between decision states. Smoothness is a property of fuzzy rule-based systems not often achieved in standard rule bases unless a great many rules are used.

---

Insert Figure 7

---

### **3.5 System Platform**

This system does not require any special hardware platform other than the standard WINDOWS environment on a PC. Pull down menuing and windowing capabilities are supplied by Visual Basic to provide a familiar interface to the user. The system requires no special user expertise to implement or use the system. This was done purposefully to accommodate the

---

are of the same state.

limited computing facilities in the plant and the variety of users. Visual Basic provides the user interface and the integration architecture. The data repository was built in Microsoft Access. The neural network models were developed using Brainmaker Professional, a neural network development software package, and the completed models were translated to compiled ANSI C code. The optimization algorithm was developed and compiled in C. The fuzzy logic rule bases were developed using Togai Infracore's TILShell software package, version 3.0.1. The expert system was then compiled into a DOS executable file using the package's C code generation capabilities.

#### **4. CONCLUSIONS**

This hybrid modular system is the first known comprehensive decision support system using computational intelligence for the ceramic slip-casting process. The integration of neural networks, an optimization algorithm and the fuzzy logic rule bases allow modeling of the highly non-linear relationship among the process variables and the capture of qualitative factors and expert knowledge from plant personnel. Utilization of the system enables casting decisions to be made consistently and correctly without the need for judgmental speculation or expensive trial-and-error test casts. This case study demonstrates that the newer computational approaches can be of value even in what have traditionally been regarded as "low tech" processes, such as slip-casting. This system does not require any special hardware or software, or any particular expertise on the part of the user. In fact, the technologies behind the system have purposefully been kept hidden to the user.

From a generic hybrid systems viewpoint, the most interesting aspect of this research is that the three approaches work in a truly integrative manner. The neural networks serve as both an objective function evaluator for the optimization algorithm and as an estimator of an input

needed by the fuzzy rule base. Because of the dependence of the system on the neural network predictions, validation was as stringent as possible. The users had to be assured that the predictions of cast rate and moisture gradient were sufficiently accurate over the range of operation of the plant. This was accomplished through empirical validation using the group cross validation method so that all data contributed to both the final predictive models and the validation effort.

### **Acknowledgement**

Part of this work was supported by the Ben Franklin Technology Center of Western Pennsylvania and the U.S. National Science Foundation grant DMI 9501234 CAREER.

## REFERENCES

- Adams, E. F. (1988) Slip-Cast Ceramics. *Introduction to the Principles of Ceramic Processing* (J. S. Reed, editor), John Wiley & Sons, Inc., Chapter 7, New York.
- Azouzi, R. and Guillot, M. (1996) Control and Optimization of the Turning Process Using a New Hybrid Neural Network. *Proceedings of the Japan/USA Symposium on Flexible Automation*, **2**, 1437-1444.
- Chen, C. D., Shi-Shang, J. and Tsen, A. Y. (1997) Semi-continuous Copolymer Composition Distribution Predictive Control Using a Double ANN Model Structure. *Journal of the Chinese Institute of Chemical Engineers*, **28**, 1, 49-59.
- Chong, E. K. P. and Zak, S. H. (1996) *An Introduction to Optimization*. John Wiley & Sons, New York.
- Coit, D. W., Jackson, B. T. and Smith, A. E. (1998) Static Neural Network Process Models: Considerations and Case Studies. *International Journal of Production Research*, **36**, 2953-2967.
- Dinger, D. R. (1990) Expert Systems for use in Ceramic Processing. *Ceramic Engineering and Science Proceedings*, **11**, 320-331.
- Efron, B. (1982) *The Jackknife, the Bootstrap and Other Re-sampling Plans*. SIAM, Philadelphia.
- Funahashi, K. (1989) On the Approximate Realization of Continuous Mappings by Neural Networks. *Neural Networks*, **2**, 183-192.
- Geman, S., Bienenstock, E. and Doursat, R. (1992) Neural Networks and the Bias/Variance Dilemma. *Neural Computation*, **4**, 1-58.

Hornik, K., Stinchcombe, M. and White, H. (1989) Multilayer Feed-forward Networks are Universal Approximators. *Neural Networks*, **2**, 359-366.

Knotts, W. (1995) Ball Clay Selection Using Experimental Design Techniques. *Ceramic Engineering and Science Proceedings*, **16**, 123-126.

Lambe, C. M. (1958) Preparation and Use of Plaster Molds. *Ceramic Fabrication Processes* (W. D. Kingery, editor), John Wiley & Sons, Inc., Chapter 3, New York.

Lin, C. M., Chu, T. K. and Chang, T. P. (1996) Cement Roller Mill Control by Fuzzy Logic Controller. *Journal of Control Systems and Technology*, **4**, 2, 133-138.

Martinez, S. E., Smith, A. E. and Bidanda, B. (1994) Reducing Waste in Casting with a Predictive Neural Model. *Journal of Intelligent Manufacturing*, **5**, 277-286.

Montgomery, D. C. and Runger, G. C. (1994) *Applied Statistics and Probability for Engineers*. John Wiley & Sons, New York.

Petri, K. L. and Smith, A. E. (1996) A Hierarchical Fuzzy Model for Predicting Casting Time in a Slip-Casting Process. *Proceedings of the Fifth Industrial Engineering Research Conference*, Minneapolis, MN, May, 217-222.

Readey, M. J. (1993) Optimized Processing of Advanced Ceramics: A Case Study in Slip Casting Y-TZP. *Ceramic Engineering and Science Proceedings*, **14**, 288-297.

Reeves, C. R. (editor) (1993) *Modern Heuristic Techniques for Combinatorial Optimization*. John Wiley & Sons, New York.

Ross, Timothy J. (1995) *Fuzzy Logic with Engineering Applications*. McGraw-Hill, New York.

Saaty, T. (1980) *The Analytic Hierarchy Process*. McGraw-Hill, New York.

Shin, Y. C. and Vishnupad, P. (1996) Neuro-fuzzy Control of Complex Manufacturing Processes. *International Journal of Production Research*, **34**, 12, 3291-3309.

Stinson, M. E., Lee, O. W., Steckenrider, J. S. and Ellingson, W. A. (1994) Recognition Of Subsurface Defects In Machined Ceramics By Application Of Neural Networks To Laser Scatter Patterns. *Ceramic Engineering and Science Proceedings*, **15**, 390-396.

Twomey, J. M., Smith, A. E. and Redfern, M. S. (1995) A Predictive Model for Slip Resistance Using Artificial Neural Networks. *IIE Transactions*, **27**, 374-381.

Twomey, J. M. and Smith, A. E. (1998) Bias And Variance Of Validation Methods For Function Approximation Neural Networks Under Conditions Of Sparse Data. *IEEE Transactions on Systems, Man, and Cybernetics, Part C*, **28**, 417-430.

Wolpert, D. H. (1993) Combining Generalizers by Using Partitions of the Learning Set. *1992 Lectures in Complex Systems* (L. Nadel and D. Stein, editors), SFI Studies in the Sciences of Complexity, Lect. Vol. V, Addison-Wesley.

Xia, Z., Lai, S., Hu, Z. and Lu, Y. (1995) Database and Knowledge Acquisition for Ceramics Design. *Computerization and Networking of Materials Databases: Fourth Volume, ASTM STP 1257* (C. P. Sturrock and E. F. Begley, editors), American Society for Testing and Materials, Philadelphia, 224-234.

Zhang, H. C. and Huang, S. H. (1995) Applications of Neural Networks in Manufacturing: A State of the Art Review. *International Journal of Production Research*, **33**, 705-728.

Table 1. Slip Casting Process Parameters.

<b>Input</b>	<b>PARAMETER</b>	<b>DEFINITION</b>
1	Plant Temperature (°F)	The temperature of the plant.
2	Relative Humidity (%)	The humidity level of the plant.
3	Cast Time	The time the liquid slip is left in the mold before draining.
4	Sulfate (SO <sub>4</sub> ) Content	Proportion of soluble sulfates in the slip.
5	Brookfield - 10 RPM	Viscosity of the slip at 10 revolutions per minute.
6	Brookfield - 100 RPM	Viscosity of the slip at 100 revolutions per minute.
7	Initial Reading	Initial viscosity (taken at 3 1/2 minutes).
8	Build Up	Change in viscosity from initial reading (taken after 18 minutes).
9	20 minute Gelation	Thixotropy (viscosity versus time).
10	Filtrate Rate	The rate at which the slip filtrates.
11	Slip Cake Weight	Approximation of the cast rate without considering a mold.
12	Cake Weight Water Retention	Moisture content of the cake. See slip cake weight.
13	Slip Temperature	The temperature of the slip.

Table 2. MAE, RMSE and Percent Correct of MGNN.

<b>Category</b>	<b>Moisture Gradient Range</b>	<b>Number of Observations</b>	<b>Number of Correct Predictions</b>	<b>Percent Correct</b>	<b>MAE</b>	<b>RMSE</b>
1	< 0.005	272	220	80.88	0.001904	0.002647
2	0.005-0.010	53	23	43.40	0.002243	0.002817
3	0.010-0.020	24	14	58.33	0.003952	0.004758
4	0.020-0.030	9	6	66.67	0.004978	0.006430
5	> 0.030	9	5	55.56	0.015485	0.021231

Table 3. Distribution of Incorrect Predictions of MGNN.

<b>Number of Categories Away</b>	<b>Number of Observations</b>
1	89
2	9
3	1
4	0

Table 4. FAM for Mold Condition.

<b>Temperature</b>	<b>Humidity / Age</b>								
	Low			Medium			High		
	<i>New</i>	<i>Mid</i>	<i>Old</i>	<i>New</i>	<i>Mid</i>	<i>Old</i>	<i>New</i>	<i>Mid</i>	<i>Old</i>
Low	Dry	Dry	AvgWet	Avg	AvgWet	VeryWet	AvgWet	Wet	VeryWet
Medium	VeryDry	Dry	AvgWet	Dry	Avg	Wet	AvgDry	AvgWet	VeryWet
High	VeryDry	VeryDry	Avg	VeryDry	Dry	AvgWet	AvgDry	AvgWet	Wet

Table 5. FAM for Cast Time.

	<b>Mold Condition</b>						
<b>Cast Rate</b>	VeryDry	Dry	AvgDry	Average	AvgWet	Wet	VeryWet
Low	Avg	Short	AvgShort	Avg	AvgLong	Long	Longest
Medium	Short	Short	AvgShort	Avg	AvgLong	Long	Long
High	Shortest	Shortest	Short	Short	AvgShort	Avg	AvgLong

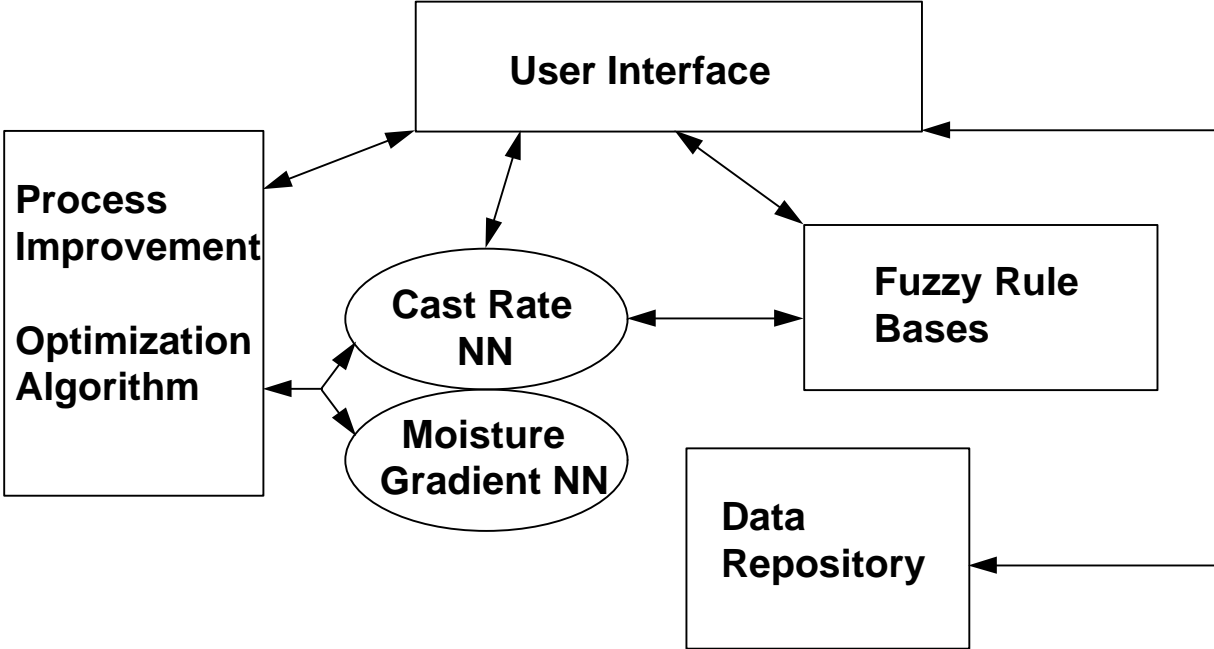


Figure 1. Block Diagram of the Hierarchical System.

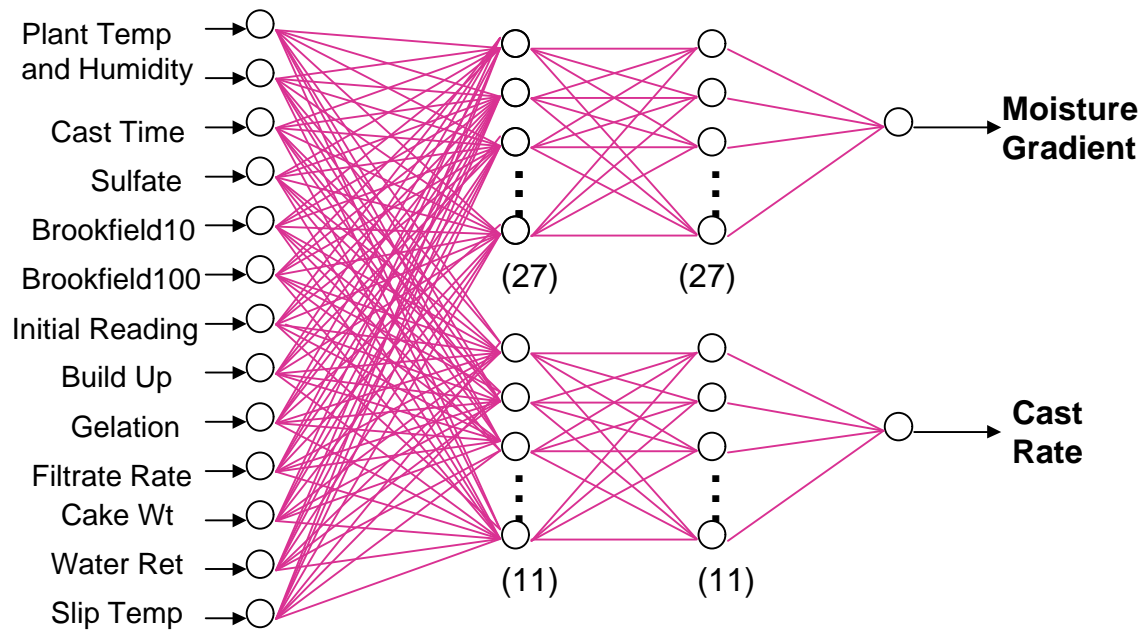


Figure 2. Neural Network Prediction Module.

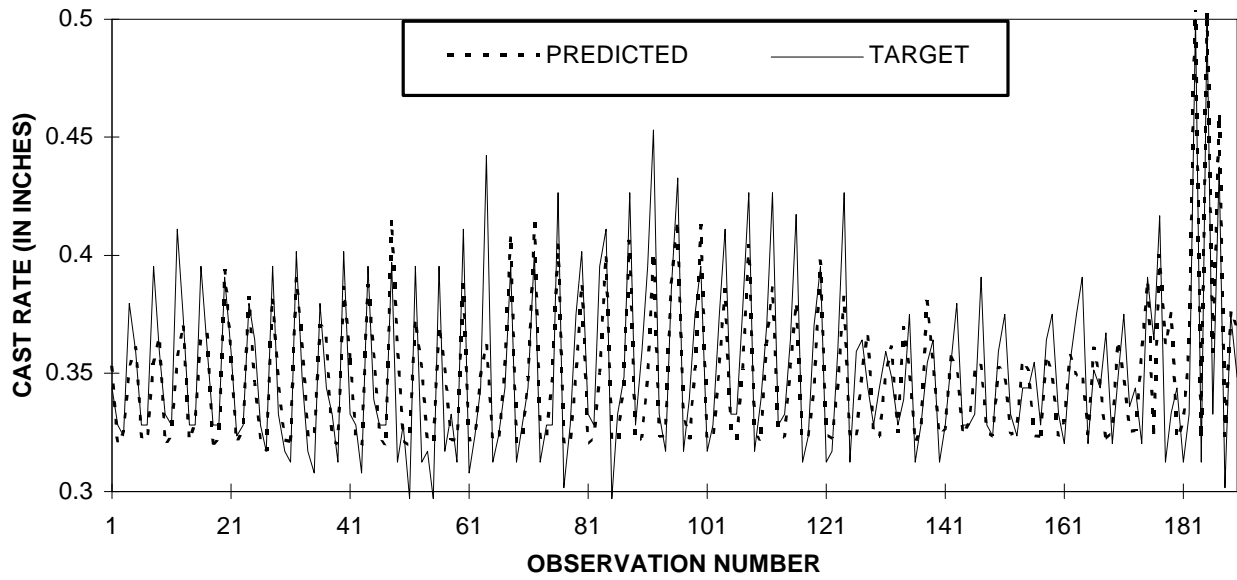


Figure 3. Performance on a 20% Cross Validation: Predicted Against Target Cast Rate.

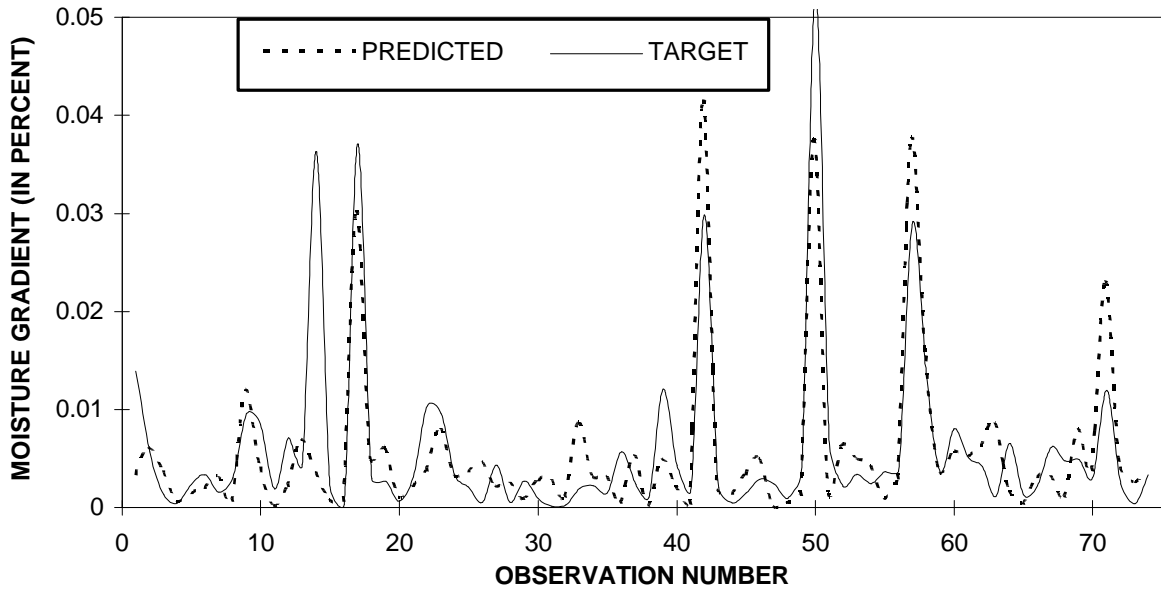


Figure 4. Performance on a 20% Cross Validation: Predicted Against Target Moisture Gradient.

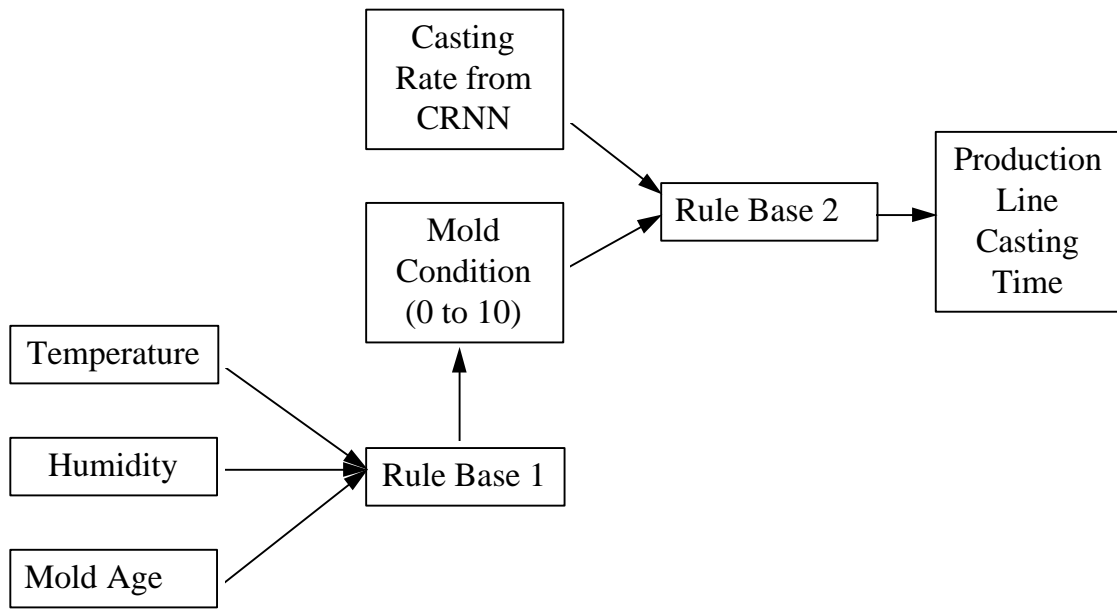


Figure 5. Structure of the Fuzzy Logic Expert System Module.

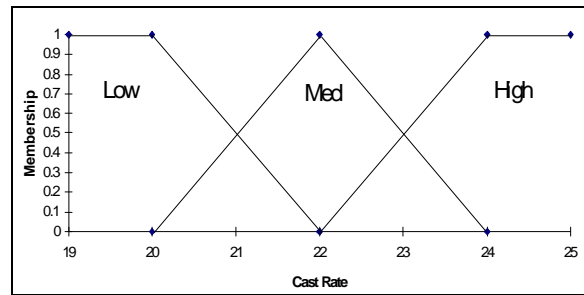
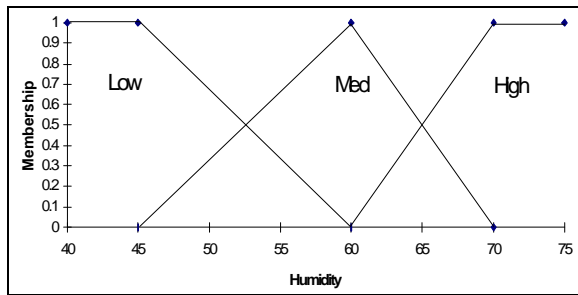
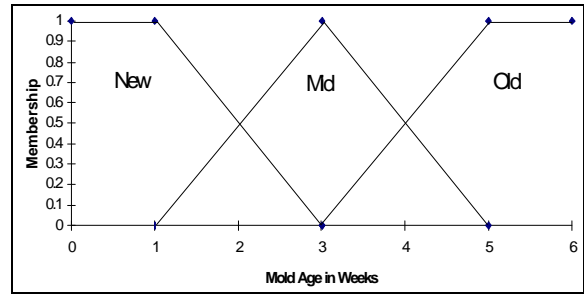
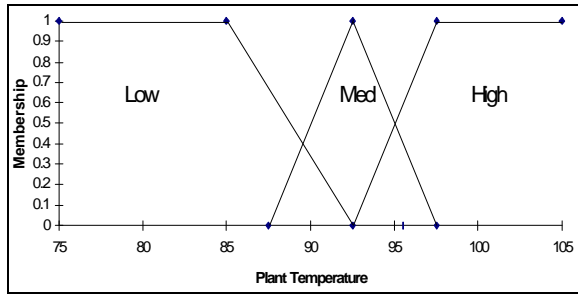


Figure 6. Some of the Membership Functions in the Fuzzy Expert System.

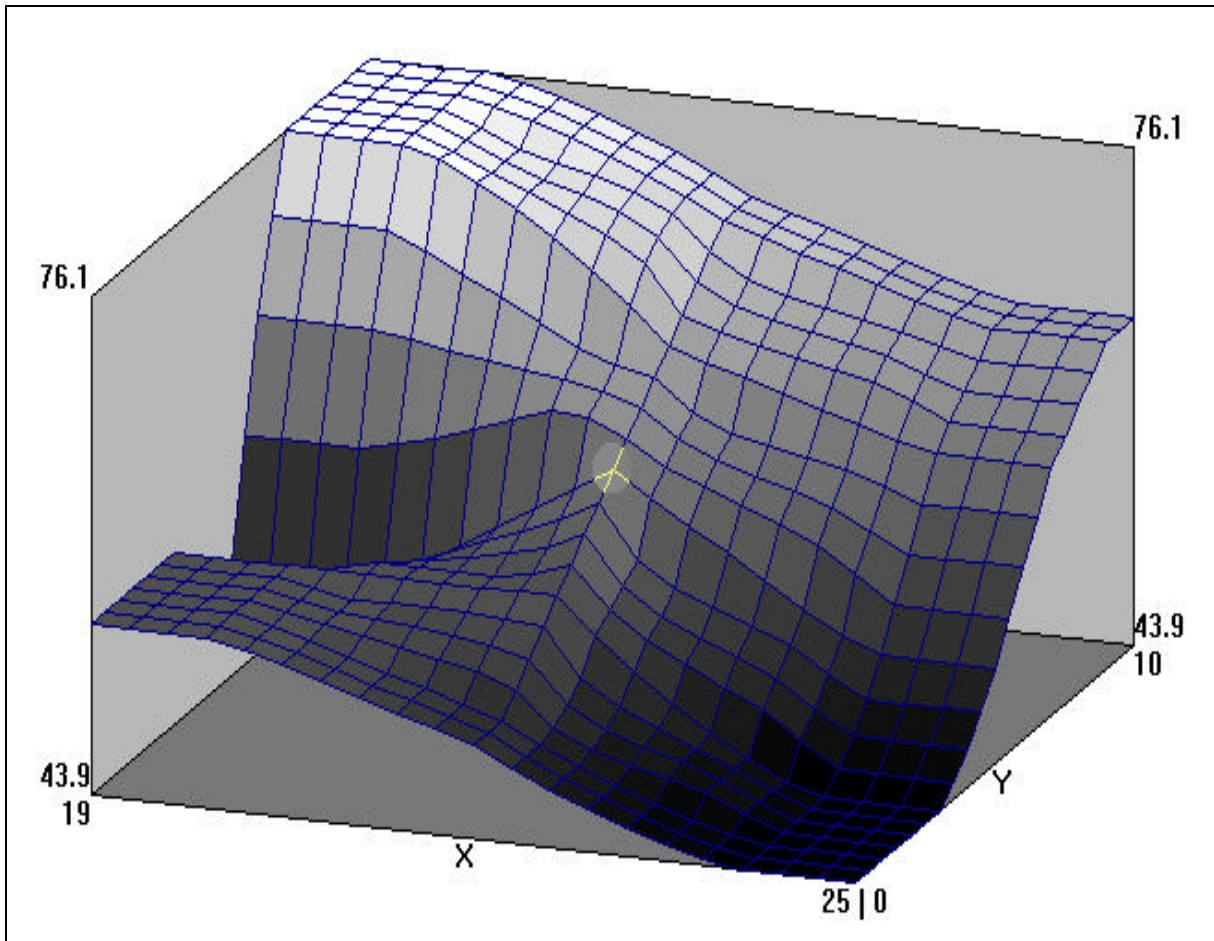


Figure 7. Decision Surface for Cast Time Rule Base with Cast Time (in minutes) ( $z$ ) vs. Cast Rate (in inches) ( $x$ ) and Mold Condition (ordinal scale) ( $y$ ).

## Author Biographies

**Sarah S. Y. Lam** is Assistant Professor in the Department of Systems Science and Industrial Engineering at Binghamton University (S.U.N.Y.). She received a B.A. (HONS) in Quantitative Analysis for Business from City University of Hong Kong, an M.S. in Operations Research from the University of Delaware, and a Ph.D. in Industrial Engineering from the University of Pittsburgh in 1999. Her research interests are in the areas of neural network modeling of manufacturing processes, evolutionary optimization and data mining. She is a member of IIE, INFORMS and IEEE.

**Kimberly L. Petri** received a B.S. in Mathematics from Grove City College (Grove City, PA) and an M.S. in Industrial Engineering from the University of Pittsburgh. Her interests are in intelligent manufacturing especially neural networks and fuzzy logic. She is currently employed by Wisewire Inc. in Pittsburgh.

**Alice E. Smith** is Professor and Chair of Industrial and Systems Engineering at Auburn University. She was with the Industrial Engineering Department of the University of Pittsburgh from 1991 through 1999. Her research in analysis, modeling and optimization of manufacturing processes and engineering design has been funded by the National Institute of Standards (NIST), Lockheed Martin, ABB Daimler-Benz Transportation (Adtranz), the Ben Franklin Technology Center of Western Pennsylvania and the National Science Foundation (NSF). Dr. Smith has authored over 100 publications in books, refereed proceedings and journals including articles in *IIE Transactions*, *IEEE Transactions on Reliability*, *INFORMS Journal on Computing*, *International Journal of Production Research*, *IEEE Transactions on Systems, Man, and Cybernetics*, *The Engineering Economist*, and *IEEE Transactions on Evolutionary Computation*.

Dr. Smith is a senior member of IIE, IEEE and SWE, a member of Tau Beta Pi, INFORMS and ASEE, and a Registered Professional Engineer in Industrial Engineering.